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An integrated approach to gender equality, diversity, and inclusion in the development of artificial intelligence tools in agriculture and food system in Africa

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Abstract
Agriculture in sub-Saharan Africa faces complex challenges, such as low productivity, climate stress, and ongoing social inequalities, particularly affecting women and marginalised groups. Whilst artificial intelligence (AI) holds transformative potential for agriculture and food systems, its development often overlooks these stakeholders, thereby reinforcing existing disparities. This study investigates two AI research initiatives in Nigeria and Uganda that employed a design-by-inclusion approach rooted in gender equality, diversity, and inclusion (GEDI) principles. Through retrospective case studies involving small groups of women and persons with disabilities, we examine how participatory engagement influenced the relevance, usability, and confidence of AI tools amongst users. Drawing on insights from Feminist Human–Computer Interaction (HCI) and Design Justice, our analysis demonstrates that inclusive processes led to significant improvements in participants' confidence and willingness to engage with AI tools. Based on these findings, we propose a practical framework for developing inclusive AI in agriculture. This work underscores the importance of context-sensitive, participatory design in fostering equitable and effective AI innovations within African agriculture.

Keywords Design-by-inclusion · Inclusive design · Responsible AI · AI in agriculture · Gender equality · Diversity and inclusion

1 Introduction

Achieving agricultural transformation remains one of Africa's most urgent priorities, yet it has proven to be a significant challenge (Tsan et al. 2019). According to Goedde et al. 2019, Africa, especially sub-Saharan Africa (SSA), needs to at least double, and possibly triple, its current agricultural productivity levels to meet the continent's growing population demand and prevent food and nutrition insecurity. The continent must achieve these targets whilst also adapting to the impacts of climate change (Cowls et al. 2023). Climate change is already affecting the agricultural sector through increased climate volatility and the damaging effects of droughts, floods, pests, and diseases. Given these high

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stakes, it is unsurprising that most African countries have prioritised agricultural transformation as a key element of their national strategies (Jayne et al. 2021). In this context, artificial intelligence (AI) in agriculture and food systems has the potential to act as a catalytic force, supporting and accelerating agricultural transformation across the continent (Arakpogun et al. 2021; Adebola and Ibeke 2023). Artificial intelligence refers to a range of technologies that enable machines to operate intelligently, mimicking human sensing, understanding, and action (Li et al. 2018). AI encompasses various technologies, including machine learning, computer vision, robotics, and data analytics, which can be applied throughout the agricultural value chain, from enhancing crop production to distribution, marketing, and consumption (Dwivedi et al. 2021; Soori et al. 2023).

The application of AI tools in African agriculture and food systems (AFS) is still in its infancy. However, there are several information and communication technology (ICT) and digital innovations that are in use in AFS across sub-Saharan Africa that are not necessarily artificial intelligence tools by definition, but potentially lay the groundwork for the AI ecosystem. There are more than 400 digital agriculture solutions in use in SSA, with applications in financial services, market linkages, agricultural advisory and information services, and supply chain management (Tsan et al. 2019). In particular, mobile phones and short message service (SMS) have emerged as popular digital tools being utilised by smallholder farmers in various countries in sub-Saharan Africa (Kudama et al. 2021). In Niger, for instance, mobile phones were found to reduce farmers' search costs for agricultural price information by 50% (Aker and Mbiti 2010), Similarly, in Nigeria, SMS text reminders to farmers increased their farm productivity (Sennuga et al. 2020). Interactive voice response systems, such as those used for groundnut farmers in Tanzania, provide automated agricultural advice tailored to farmers' queries (Ortiz-Crespo et al. 2021). Digital platforms are also facilitating market linkages and financial inclusion in SSA. Companies like Twiga Foods, a Kenyan agritech and logistics company, connect rural fruit and vegetable farmers directly with urban vendors, eliminating intermediaries (Kumar and Perepu 2017). Other similar ICT digital solutions include the EzyAgric digital platform in Uganda that addresses challenges faced by farmers and other value chain actors in accessing extension services, markets, financial products, weather information, and supply chain management (Ajambo et al.). The EzyAgric platform is accessible via a mobile app or through a network of community-based service providers equipped with smartphones, allowing farmers without access to them. The Esoko platform in Ghana provides automated alerts containing information sent to mobile phones in the form of SMS and voice messages about market prices of commodities across various markets nationwide, weather forecasts, crop price bids, and crop production protocols (Van Schalkwyk et al. 2017; Etwire et al. 2017).

Whilst digital innovations in agriculture hold promise in SSA, their widespread scale-up faces challenges on the demand side, such as poor digital literacy, high costs of digital technology, and language and cultural barriers. From the supply side, barriers include a lack of supporting infrastructure, limited enabling policies and user engagement at product development (Arakpogun et al. 2021). The ability to utilise AI innovation is a function of multiple factors that are deeply gendered and often socially exclusionary, including education, digital literacy, technological and structural competence, and access to resources. These usually do not favour women and other marginalised farmers, such as persons living with disabilities (Rohman and Vo 2024). In addition, AI tool designers may unintentionally hold gender and social biases and fail to recognise the diverse needs of users or the importance of inclusive user engagement. (Fan et al. 2024). Consequently, the application of AI in agriculture is likely to exacerbate existing gender and social disparities unless mitigation measures are implemented. Addressing these inequities in access to and use of AI tools is essential to ensure that these technologies benefit all farmers, particularly women and marginalised groups, equitably.

A study by the Technical Centre for Agricultural and Rural Cooperation (CTA) on the digitalisation of African Agriculture, conducted in 2018–2019, reported country case studies that showed lower levels of women using digital tools in agriculture in sub-Saharan Africa (Table 1).

The percentage of women users of digital tools is clearly low, ranging from 10% in Senegal to 30% in Ghana (Table 1). However, as AI gains traction in African agriculture, there is an opportunity to engage better and empower Africa's women, who constitute an estimated 40–50% of the continent's smallholder farmers (Livingston et al. 2011). Besides, responsible AI requires that nobody is left behind or is discriminated against and that all benefit from the potential of AI. (Plantinga et al. 2024). Many digital tools are created with little consideration for the diverse needs of users or varying contexts in which they are used (Emeana et al. 2020). Unless the needs and priorities of women, young people and persons with disabilities in agriculture are considered in the AI design processes, these tools and therefore the benefits will continue to replicate and reinforce existing exclusions, based on assumptions about stereotypical users (Patrick and Hollenbeck 2021). Adopting a user-led, inclusive design approach in AI development offers a way to counter these limitations. For digital tools to be meaningfully adopted, they must create clear and tangible value for farmers that aligns with their diverse needs. Yet, many existing tools fail to demonstrate immediate benefits or returns on investment (Dittmer et al. 2022). Furthermore, such tools must provide information, advice and solutions

Table 1 Digital agriculture solutions for country case studies in sub-Saharan Africa, along with the percentage of women users, according to a study by the Technical Centre for Agricultural and Rural Cooperation (CTA) on the digitalisation of African Agriculture (2018–2019)

Country	No. of solutions	Total users	Women users	Primary use
Ghana	28 headquartered 57 with a presence	1.6million	30%	Advisory services Market linkages Supply chain management
Kenya	64 headquartered 114 with a presence	9.0million	28%	Advisory services Market linkages Financial inclusion
Nigeria	46 headquartered 83 with a presence	0.5million	20%	Data intermediary Market linkages
Ethiopia	4 headquartered 29 with a presence	5 million	17%	Advisory services
Senegal	15 headquartered 43 with a presence	400,000 +	10%	Advisory services Market linkages
Rwanda	8 headquartered 44 with a presence	3.5million		Advisory services
Sahel region	28 headquartered 92 with a presence	5.7million		Advisory services

Source: (Tsan et al. 2019)

that are contextually relevant and tailored to users' environments, interests and challenges with explicit attention to gender and social differences (Bonina et al. 2021).

To ground this inclusive design imperative in theory, we draw on feminist technology studies, participatory design, and digital inclusion frameworks. Bardzell's Feminist Human–Computer Interaction (HCI) emphasises pluralism, participation, and reflexivity in design, offering a valuable lens to examine how AI tools may reproduce or disrupt gendered power dynamics (Bardzell 2010). Similarly, Costanza-Chock's Design Justice framework critiques top-down innovation models and advocates for co-design with communities that have been historically marginalised in technological development (Costanza-Chock 2020). These frameworks align with our design-by-inclusion approach, which seeks to emphasise equity and user empowerment throughout the AI development process. Against this background, the overall objective of this paper is to provide a practically and theoretically grounded approach to incorporating Gender Equality, Diversity, and Inclusion (GEDI) into AI development for agriculture and food systems (AFS) in Africa. Drawing lessons from two AI research projects implemented under the Artificial Intelligence for Development (AI4D) Africa initiative in Nigeria and Uganda, we examine how a design-by-inclusion approach can foster equitable AI innovation without exacerbating gender gaps or reinforcing structural inequalities.

Design-by-inclusion, as conceptualised in this study, builds on established frameworks, such as participatory design, co-production, co-design, and inclusive innovation. Participatory design focuses on involving users early and throughout the design process to ensure that technologies reflect their needs and contexts (Wacnik et al. 2025). Co-production and co-design emphasise the joint creation of knowledge and solutions by researchers and intended beneficiaries, fostering mutual learning and shared ownership (Benz et al. 2024) whilst inclusive innovation seeks to ensure that both the process and outcomes of innovation benefit marginalised or disadvantaged groups (Shams et al. 2025). Our approach extends these traditions by systematically embedding GEDI principles at each stage of the AI development process. It aims not only for user participation, but also for structural inclusion and empowerment of women and marginalised farmers in digital agricultural transformation.

2 Methods

2.1 Design-by-inclusion approach case studies

This study was conducted within ongoing AI research projects based in sub-Saharan Africa, specifically in Uganda (East Africa) and Nigeria (West Africa). The aim was to explore how the inclusion of marginalised groups, particularly women and persons living with disabilities (PLWDs), in the design and development of AI technologies could enhance their adoption in agriculture and food systems. The research projects from these two countries were selected from a cohort of 10 AI4AFS research teams due to their distinct characteristics. In Nigeria, the AI project focussed on pest detection of yellow pepper, with women and marginalised communities actively involved from the outset in identifying key challenges for the AI tool to address. In Uganda, this study examined a scale-up initiative where an AI tool for

the early detection of cassava diseases, originally developed under a different research programme, was being expanded for broader implementation. Thus, the AI research project in Nigeria represented a shift from traditional approaches, with inclusivity ensuring that the technology was tailored to user-specific needs, distinguishing it from the project in Uganda. This contrast enabled us to compare proactive versus adaptive GEDI integration, offering valuable insights into the impact of timing and design. Our study on design-by-inclusion in the two projects took a retrospective approach as the AI tools had already been developed prior to our assessment.

2.2 AI tools under study

The AI models studied differed by country. In Nigeria, the AI tool was a machine learning-based pest detection system employing the SSD MobileNet architecture, implemented using TensorFlow. The model was trained and tested using a dataset of 4000 images, with a 60:40 training-to-testing split and achieved an F1 score of 0.81, indicating a good balance between precision and recall in pest detection. In Uganda, the AI solution focussed on cassava disease detection, employing a convolutional neural network (CNN) model based on a pre-trained ResNet50 architecture, achieving an overall accuracy of 87%. This demonstrated strong predictive performance for disease identification. These technical models were integrated into broader inclusive design processes to align AI performance with user needs, particularly those of marginalised groups.

2.3 Sampling of study participants

Participants for the study were purposively selected based on their active involvement in the yellow pepper and cassava value chains. The selection process emphasised gender balance, inclusion of persons living with disabilities (PLWDs), and representation across different segments of the community to ensure diverse perspectives. Ethical approval for the study was obtained from the institutional review boards of the respective research organisations leading the projects.

2.4 Community dialogues

To explore the alignment between user needs and the developed AI tools, we adopted culturally and socially sensitive participatory engagement approaches. These began with community dialogue to identify priority challenges along the yellow pepper and cassava value chains. Target participants, particularly women and persons living with disabilities (PLWDs), had been identified by the research project teams using a gender-sensitive lens and in alignment with the GEDI framework promoted by the AI4AFS hub. The project teams maintained ongoing engagement with participants, fostering a relationship of trust and collaboration that facilitated testing and reflection on the design-by-inclusion process.

The dialogues were conducted in accessible community venues. In Nigeria, 25 farmers participated and were divided into five groups: four groups consisted of five women each, and a fifth group was composed of men, including persons living with disabilities (PLWDs), elderly farmers, and youth farmers. In Uganda, 24 farmers participated, with one group of 15 women and another group of nine men, including persons living with disabilities (PLWDs) and the elderly. To ensure safe and open expression, particularly for women, we established women-only safe spaces. The discussions were guided using a community conversation approach, where women interviewed women, and men interviewed men. These sessions aimed to capture farmers' experiences, challenges and perspectives across the agricultural value chain and to identify priority areas where AI-driven solutions could offer meaningful impact. Given that the AI tools had already been developed, these dialogues served as a retrospective inquiry into how well the tools aligned with users' realities and expectations, especially those of marginalised groups.

All dialogue sessions were audio-recorded with the participants' prior consent. The primary data collection method was detailed note-taking by two dedicated note-takers present in each session in Nigeria and Uganda. The note-takers were trained to capture key points, direct quotations, and observational details. Immediately following each session, the audio recordings were used to verify and augment the notes, ensuring accuracy and completeness of the information. The verified notes were then transcribed digitally into Microsoft Word for analysis. Ethical approval for this study was obtained prior to data collection from the Institutional Review Boards of the University of Nigeria, Nsukka and Busitema University, Uganda. All participants provided written or thumb-printed informed consent.

Insights from the workshops informed the refinement of the AI tools to suit farmers' needs and experiences better, whilst ensuring inclusivity. The subsequent stage involved co-developing training lessons to build the skills and competencies of marginalised groups, enabling them to use the AI tools effectively. These training lessons were designed collaboratively with participating users, AI innovators, and extension staff to ensure they specifically addressed the needs of women and marginalised communities. Following this, AI innovators led training sessions that focussed on enhancing the technical and digital skills of women and marginalised communities for the practical use of AI tools. A continuous feedback mechanism was integrated into the training process, allowing technology users to share insights that contributed to further refinement and improvement of the AI tools.

2.5 Data analysis

We employed a qualitative thematic analysis approach (Creswell & Poth 2018; Denzin & Lincoln, 2017) to analyse the data from the community dialogues. The analysis followed a structured, iterative process to ensure rigour and trustworthiness.

Familiarisation: The research team began by thoroughly reading and re-reading all transcribed notes to immerse themselves in the data.
Initial coding: Two researchers (Authors [DS, JN]) independently performed open coding on a subset of the transcripts using NVivo 12 software. This involved generating descriptive codes that captured key issues, challenges, and needs (e.g. "pest_detection_difficulty", "market_price_volatility", "women_access_phone_issue").
Development of a preliminary coding schema: The two researchers then met to compare their initial codes, resolve discrepancies through discussion, and collaboratively develop a preliminary codebook. An inter-rater reliability check was conducted on 20% of the data, achieving a Cohen's Kappa coefficient of 0.81, indicating a high level of agreement.
Application of the codebook: The agreed-upon codebook (see Appendix A) was then applied systematically to the entire dataset by the primary coders.
Theme generation: Related codes were grouped into candidate themes (e.g. "Gendered Priority Misalignment", "Digital Access Barriers", "Training Efficacy") that captured broader, significant patterns across the data.
Review and refinement of themes: The research team reviewed the candidate themes against the coded data and the entire dataset to ensure they accurately represented the participants' narratives. Themes were refined and defined.
Triangulation: To enhance validity, findings were triangulated through constant comparison between the data from Nigeria and Uganda and through discussion amongst all co-authors, who brought diverse perspectives from AI, gender studies, and agricultural extension.

This rigorous process enabled a structured and credible interpretation of participant perspectives, facilitating insights into how participatory design shapes AI tool relevance and adoption."

2.6 Threats to validity

We considered potential threats to the validity of our qualitative study and implemented strategies to mitigate them, following established guidelines (Creswell and Poth 2018).

Internal validity (credibility): This refers to the accuracy of the findings. A potential threat was researcher bias as the team was invested in the success of the inclusive design approach. To mitigate this, we employed triangulation by analysing data from two different country contexts and involving multiple researchers in the analysis to challenge our interpretations. We also employed member checking by summarising and sharing key findings with a subset of participants to confirm our interpretations resonated with their experiences.

Construct validity (dependability): This refers to whether we accurately measured the concepts under study. A threat was the potential for social desirability bias, where participants might tell us what they thought we wanted to hear. To mitigate this, we ensured confidentiality and used local facilitators in single-gender groups to create a safer environment for honest dialogue. The use of audio recordings and detailed notes also ensured we accurately captured what was said.

Whilst the retrospective nature of the study is a limitation (as noted in the discussion), the strategies above strengthen the credibility and dependability of our findings within the studied contexts.

3 Results

3.1 Problem identification—Uganda case

In the Uganda case study, gender differences emerged in the priorities identified by women and men cassava farmers regarding the needs AI should address. When asked to rank their priority needs, women farmers placed the highest importance on soil nutrient analysis, both for assessing suitability for cassava production and detecting disease-causing pathogens to guide variety selection. One female participant explained, *"We can see the disease on the leaves, but we cannot see the sickness in the soil. If the tool could tell me my soil is poor or has harmful germs [pathogens], that would be most helpful before I even plant. (Kwikiriza Phiona, cassava farmer, Uganda).* Their second priority was identifying diseases and pests, along with strategies for intervention and control. The third was market access and price management, including the establishment of cooperative societies to improve bargaining power. In contrast, men farmers identified unstable market prices as their top concern. These differences highlight the importance of incorporating diverse user perspectives in problem definition and solution design. Without a gender equitable and inclusive (GEI) approach, AI innovations risk misalignment with user needs and may inadvertently reinforce existing gender and social inequities.

3.2 Problem identification—Nigeria case

In the Nigeria case study, the AI tool was co-developed with marginalised farmers, including women and persons living with disabilities (PLWDs). The women farmers highlighted three key agricultural challenges that AI tools should address, in order of priority. First, pest and disease detection is crucial as pests and diseases pose significant threats to crop yields, making advanced detection and management technologies essential. Second, water management is crucial for efficient water use in sustainable farming, with farmers emphasising the need for AI-driven solutions, such as automated irrigation systems. Third, understanding soil fertility levels is vital for optimising fertiliser use and improving plant health. Women and persons living with disabilities (PLWDs) acknowledged that current AI technology was effectively meeting the need for crop pest and disease detection. They valued the benefit of receiving real-time feedback from their farms, regardless of their location. A woman living with a physical disability noted*, 'Before, I had to rely on my son to walk the farm and tell me if he saw problems. Now, I can take a picture from where I am and know immediately. It gives me back control.' (Ngozi Ugwoke, pepper farmer with disability, Nigeria)".*

3.3 Training of users and testing of AI tools

Besides the specific production needs of the participants, insights into the actual use of the AI tools showed different competence and technology needs for women, persons living with disabilities (PLWDs), and men. According to the study, more than half of the women experienced difficulties locating the data collected as images on their mobile devices. In contrast, some women did not have Android-type mobile devices that are compatible with AI applications. Our observation suggested that men had greater access to smartphones than women, with a higher proportion of men owning these devices. During the co-identification and development of training needs and materials, it became clear that low literacy on AI tool usage was a significant barrier for many women. However, the capacity training had a noticeable impact as many women expressed eagerness to use the AI tools afterwards, compared to only a few before the training. Quantitative findings support this qualitative insight: in Nigeria, willingness to use AI tools increased from 28 to 74% following GEDI-informed training, whilst in Uganda, participants' digital confidence rose by 3.2 points on a 5-point Likert scale. Field-based, hands-on training proved highly effective in boosting their confidence and willingness to adopt the technology. Felicia Ugwu, a female farmer in Nsukka, Nigeria, remarked, "*Before the training, I was afraid of the AI tool. However, now, I feel confident using it to detect pests in my crops*." Similarly, Achieng Christine, a female farmer in Uganda, shared, "*I did not even know my phone could help detect diseases in my cassava. This has opened my eyes*". *Several women expressed initial frustration with the technology. One stated, "I took the pictures, but then I could not find them again. It was like they disappeared into the phone." (Onunze Chioma, farmer, Nigeria). Another farmer in Uganda* adds, *"After the practice, it became clear. The trainer showed me step-by-step. Now I can do it myself and even showed my neighbour." (Iloka Grace, Female farmer, Uganda).* These testimonies demonstrate how inclusive training can foster digital confidence amongst marginalised farmers.

3.4 Lessons learned from the design-by-inclusion approach

Several lessons were drawn from the two case studies. Technology users must actively participate in the entire process of AI technology development, from needs identification to solution conception, product design, and development. This involvement makes the target users feel valued, heard and respected in their perspectives and opinions. Once women farmers and farmers from other marginalised groups trust the researchers and AI developers, they become integral to the technology and are more readily inclined to embrace it. Their active engagement in providing feedback further strengthens their trust in the process, fosters a sense of ownership, and helps shape the AI tool to meet their needs better.

Another critical lesson is the importance of aligning AI tools with users' highest-priority needs. In Uganda, for instance, the AI research team designed a tool focussed on early disease detection for cassava. However, users identified their top priority as soil analysis for nutrient content and pathogen detection, leading to a mismatch between the tool's design and user needs. In contrast, the Nigeria project team took a user-centred approach from the outset, consulting with farmers, particularly women, and persons living with disabilities (PLWDs) before AI development began. By integrating their priorities early in the process, the team ensured that the AI tool for yellow pepper farming aligned closely with users' most pressing concerns.

The design-by-inclusion approach empowers users through collaboration and shared learning. This method not only enhances awareness of the value of AI tools but also fosters the exchange of lived experiences, strengthening

relationships amongst the marginalised users recruited for this study. As a result, many participants expressed a desire to form cooperatives to pool resources, improve market access, and enhance their bargaining power. Another lesson learned is that a one-size-fits-all approach will only engender social bias in AI technology adoption in AFS. Different groups of farmers have different needs and access to technology. These create varying levels of knowledge and competencies, which will affect the adoption of AI tools. Younger farmers with higher education levels are more likely to adopt AI technologies. By co-developing AI tools with diverse stakeholders, this approach ensures that all farmers, regardless of their prior knowledge or technological capacities, can engage meaningfully and benefit from these innovations. Regular community dialogues and training sessions played a crucial role in bridging knowledge gaps, enhancing user skills, and fostering a space for farmers to share their experiences and needs. These interactions not only strengthened user confidence in AI technologies but also reinforced the importance of participatory design in creating solutions that work for everyone.

In Sect. 4, we present an integrated framework for gender equality, diversity and inclusion in the design, development, and deployment of AI tools, drawing on insights from our case studies.

4 Framework for gender equality and social inclusion in AI tools development

The proposed framework for gender equality, diversity, and inclusion in AI tools development in AFS is structured into three stages, namely (1) Pre-AI Development and Research, (2) Development & Research Process, and (3) Deployment Testing and Adoption stages (Fig. 1). Each stage is designed to ensure that the principles of gender equality, diversity, and inclusion (GEDI) are embedded throughout the lifecycle of the AI development and deployment process.

4.1 Stage 1: Pre-AI development and research

The Pre-AI development and research stage is anchored by the design-by-inclusion approach, ensuring that inclusivity is embedded from the outset of AI development. We outline three key actions associated with this phase.

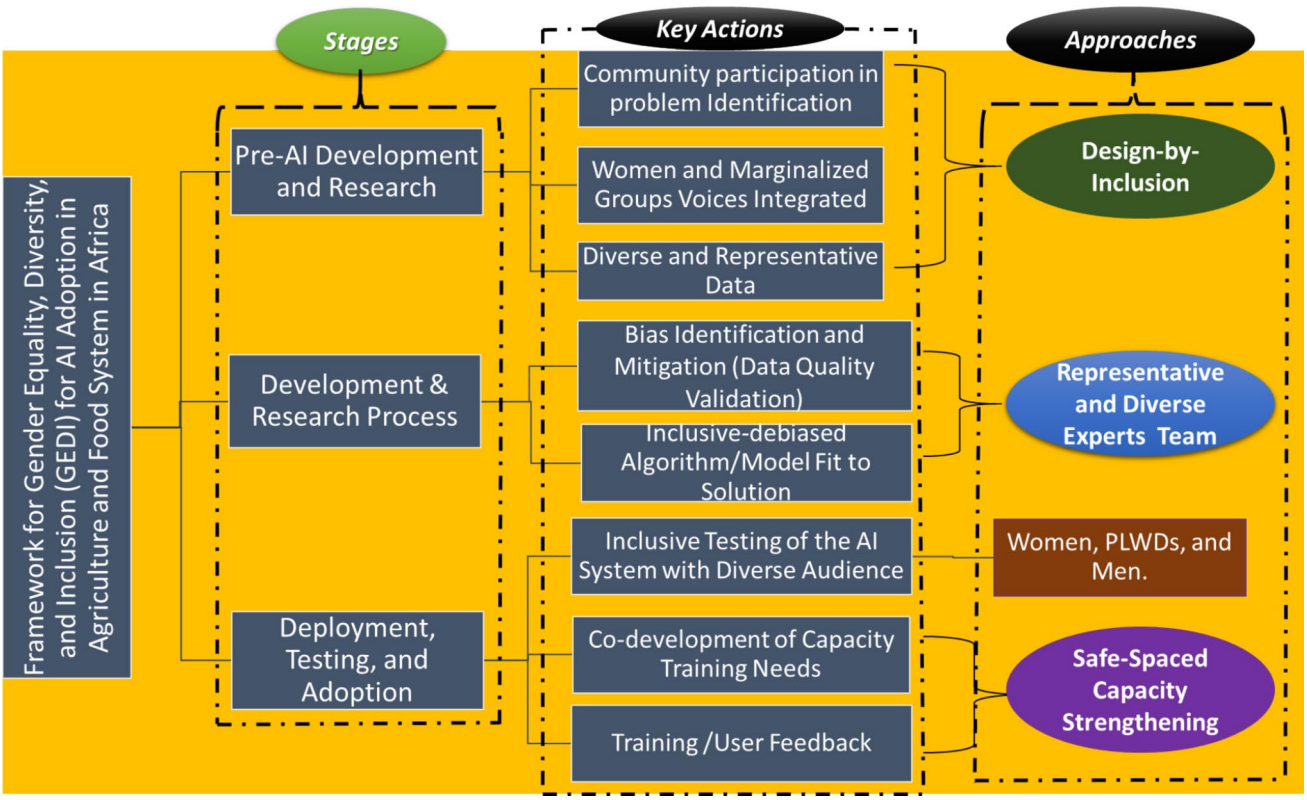

Fig. 1 Three-stage Gender Equality, Diversity and Inclusion (GEDI) framework for AI in agriculture and food systems in Africa. Stage 1: Pre-AI Development and Research, Stage 2: Development and Research Process, Stage 3: Deployment, Testing, and Adoption, with key actions for each stage and corresponding implementation approaches

4.1.1 Community participation in problem identification

This step fosters an inclusive environment where the voices of diverse user groups, particularly women and marginalised communities, are actively heard, valued and prioritised. AI innovators engage directly with target users to collaboratively identify pressing challenges and needs, ensuring that the AI solution is designed to address context-specific issues. Gender-sensitive and inclusive participatory methods, such as focus group discussions, community workshops, and dialogues, are critical in capturing diverse perspectives. Where relevant, groups should be segregated by gender and age, with safe spaces fostered to encourage open dialogue. Trust-building is essential in this stage, requiring transparent communication and a demonstrated commitment to addressing community needs.

4.1.2 Women's and marginalised groups' voices integrated

Integrating the voices of women and marginalised groups is a crucial component of the pre-AI development stage, ensuring their active participation in problem identification and decision-making processes. Intentional efforts must be made to create safe spaces where these groups can freely express themselves and discuss the issues that affect them. Beyond inclusion, their empowerment requires facilitation to ensure meaningful involvement in shaping AI solutions. Additionally, advocacy and awareness campaigns are crucial in cultivating a culture that values and prioritises inclusivity in AI. These campaigns would help raise awareness about the significance of integrating diverse voices and garner broader community support for equitable AI innovation. In our study, research projects used as case studies were required to implement a GEDI plan as a prerequisite for executing the AI projects. This structured approach ensures that gender considerations and inclusivity remain central to AI development, contributing to more equitable and effective technological solutions.

4.1.3 Diverse and representative data collection

In the pre-AI development and research stage, diverse and representative data collection is crucial to ensuring the effectiveness and fairness of AI systems. Comprehensive data strategies should be implemented to capture data that accurately reflects the diversity of the population, including gender balance and representation from various socio-economic groups. Ethical data practices must be upheld, ensuring informed consent, safeguarding privacy, and maintaining confidentiality, with special attention given to protecting vulnerable groups from exploitation and abuse. Additionally, data quality assurance is crucial, necessitating regular validation and cleaning to ensure accuracy and reliability. This process should also include identifying and mitigating biases in data collection that could compromise the fairness of AI systems.

4.2 Stage 2: development and research process

A representative and diverse team of experts is essential in AI development and research to ensure inclusivity in governance and decision-making. Assembling a multidisciplinary team that reflects diverse demographics helps identify and mitigate biases by integrating varied perspectives and expertise. Such collaboration enhances the quality and relevance of AI solutions by comprehensively addressing multiple aspects of the problem. The diversity within the team fosters innovation, promotes fairness, and ensures the development of unbiased AI models, ultimately building trust and accountability in the process. In the case of research projects under study, the teams were multidisciplinary, consisting of AI experts, crop scientists, and a gender expert in the case of Nigeria. Additionally, representatives from the user community, including women and persons living with disabilities (PLWDs), were actively involved. The development and research process involves two key actions: data quality validation and the development of inclusive and unbiased algorithms, which are described in this section.

4.2.1 Data quality validation

Ensuring data quality validation is a critical step in AI development. Bias detection methods should be employed to identify patterns that could lead to unfair assumptions, judgments, and outcomes. This involves applying advanced statistical techniques to assess the presence of bias in both data and algorithms. Once biases are identified, mitigation strategies must be implemented, which may include resampling data, adjusting algorithmic parameters, or integrating fairness constraints into the model. Continuous monitoring is necessary to detect and address any emerging biases, ensuring that the AI system remains fair and equitable over time.

4.2.2 Inclusive-debiased algorithm/model fit to solution

Developing inclusive and unbiased algorithms requires deliberate efforts to design models that are rigorously tested for fairness and accuracy. Fairness metrics and validation techniques should be applied to ensure that the algorithms do not disproportionately affect any particular group. Testing the models with diverse datasets helps us to evaluate their performance across different demographical groups,

allowing for the identification and correction of potential biases. Furthermore, transparency in model development is essential as it involves documenting and clearly communicating the steps taken to ensure fairness, thereby fostering trust and accountability in AI systems.

4.3 Stage 3: deployment, testing, and adoption

The successful implementation of AI innovations in AFS requires a structured approach to deployment, rigorous testing, and strategies for adoption in designed, inclusive, and safe spaces (Bruhn et al. 2024). Thus, to ensure the effective deployment, testing, and adoption of AI innovations in agriculture and food systems, it is essential first to build inclusive and supportive environments where diverse users can develop the necessary skills and confidence to engage with these technologies. The safe-space capacity strengthening approach (Sadeghi et al. 2023; Bruhn et al. 2024) plays a crucial role in this process by creating learning environments free from discrimination and harassment, particularly for women and marginalised groups. By providing continuous education, mentorship, and peer support, this approach equips users with the knowledge and confidence necessary to interact effectively with AI tools. These foundational capacities enhance the ability of diverse stakeholders to participate meaningfully in deployment and testing phases, ensuring that AI solutions are inclusive, practical, and widely adopted across different user groups. Therefore, integrating safe-space capacity strengthening into the AI development pipeline not only empowers users but also enhances the sustainability and success of AI adoption in agriculture. Three key actions in Stage 3, namely, Deployment, Testing and Adoption of the AI tool, are described as follows.

4.3.1 Inclusive testing of the AI system with a diverse audience

To ensure the AI system is inclusive and effective across diverse user groups, extensive field testing should be conducted with a broad audience, including women, persons living with disabilities (PLWDs), and other marginalised communities. Testing the system in real-world conditions helps validate its functionality and ensures it meets the needs of all intended users. A user-centred approach is crucial during this process, incorporating feedback from diverse participants to refine and enhance the system's accessibility and usability. Additionally, an iterative testing framework should be implemented, where continuous feedback is gathered and integrated into system improvements. This adaptive process allows the AI tool to evolve based on user experiences, ultimately making it more responsive, inclusive, and practical for widespread adoption.

4.3.2 Co-development of capacity training needs

The co-development of capacity training needs involves a collaborative approach to designing training programmes that cater for the specific requirements of diverse community groups. Engaging stakeholders in the development process ensures that the training is both relevant and accessible, enhancing participants' ability to utilise AI tools effectively. To promote inclusivity, training materials should be culturally appropriate, incorporating local languages and relatable examples to facilitate understanding amongst different user groups. Additionally, skill-building workshops should be organised to provide hands-on, interactive sessions that equip participants with practical knowledge of the AI system. This approach fosters engagement, empowers users, and enhances their ability to effectively integrate AI solutions into their work.

4.3.3 Training/user feedback

To enhance user engagement and ensure the effective utilisation of the AI system, it is essential to establish continuous learning programmes that keep users informed about new features and system enhancements. Providing ongoing training enables users to maximise the technology's potential and adapt to any updates seamlessly. Additionally, integrating structured feedback mechanisms, such as community dialogues, focus groups, and online platforms, allows users to share their experiences, report challenges, and offer suggestions for improvement. A responsive support system is also crucial in addressing user concerns promptly, fostering confidence in the AI tool, and ensuring a seamless user experience.

5 Discussion

Artificial intelligence (AI) is rapidly transforming global agriculture, offering novel solutions for yield prediction, pest detection, soil analysis, and resource optimisation (Dwivedi et al. 2021; Delfani et al. 2024). However, as technology advances, concerns persist about whether AI innovations are equitably designed and implemented, particularly in regions such as sub-Saharan Africa, where social inequalities and infrastructure gaps are pronounced. This study highlights how the benefits of AI in agriculture remain unevenly distributed, often failing to reach marginalised communities, especially women and persons living with disabilities (PLWDs), due to exclusionary design processes and limited access (Bonina et al. 2021; Plantinga et al. 2024).

Our findings underscore that contextual misalignment remains a significant barrier to the adoption of meaningful AI. In Uganda, despite good intentions, the AI tool

prioritised disease detection when women farmers identified soil nutrient analysis as their highest concern. This illustrates how top-down technology development risks creating solutions that are technically sophisticated but practically irrelevant (Halford and Savage 2010; Van Dijck et al. 2018). This is not merely a usability issue; it is a structural design failure. According to *Feminist Human–Computer Interaction* (Bardzell 2010), such mismatches often reflect the designers' assumptions rather than the lived realities of diverse users. In agricultural contexts, these assumptions tend to centre on male, literate, well-resourced farmers, inadvertently sidelining the voices and priorities of others. In contrast, the Nigeria case demonstrated that a design-by-inclusion approach anchored in GEDI principles helped surface user priorities early in the AI development process. Through participatory methods such as community dialogues, farmers shaped the technology based on their real-world challenges. Women and persons living with disabilities (PLWDs), who are often treated as passive beneficiaries, became co-creators of innovation. This aligns with the *Design Justice* framework (Costanza-Chock 2020), which critiques extractive, one-size-fits-all models and advocates for co-design that reflects the experiences of those most affected by systemic inequality.

The result of this inclusive process was not only a more contextually relevant AI tool but also increased user confidence and ownership. Participants expressed greater willingness to adopt the technology and suggested forming cooperatives to enhance collective agency, highlighting the social ripple effects of inclusive innovation. As Wajcman 2007 and Eubanks 2018 argue, the social shaping of technology is as critical as its technical design; when communities participate in innovation, they also reshape power dynamics and knowledge hierarchies. However, structural constraints persist. Our study found apparent gender gaps in smartphone access and digital literacy, reflecting broader patterns of adverse digital incorporation (Heeks 2022). These barriers are further compounded by financial exclusion. Many women farmers face difficulties in accessing capital to acquire and maintain digital tools (Mpofu 2023). As such, even well-designed AI solutions risk underutilization if complementary investments in skills development, digital infrastructure, and inclusive financing are not made. These insights echo the recommendations of Sadeghi et al. 2023 and Bruhn et al. 2024 on the need to create safe, inclusive learning environments that support marginalised users throughout the AI lifecycle, not just at the point of rollout.

From a policy perspective, our findings have several implications. First, donor and government-supported AI initiatives in agriculture must move beyond pilot projects and embed inclusive design frameworks, such as the GEDI framework proposed in this study, into national digital agriculture strategies. Whilst policy documents often reference inclusivity, they lack clear operational pathways to achieve it (FAO 2021; Jarial and Sachan 2021). Our empirical evidence suggests that involving marginalised groups in AI development is not only ethical but also leads to better-designed tools and a higher likelihood of sustained adoption. Second, gender-responsive monitoring and evaluation systems should be established to track how different social groups engage with AI tools and whether intended benefits are equitably distributed (Patrick and Hollenbeck 2021).

This study has a key limitation in that it was conducted retrospectively, after the AI tools had already been developed and partially deployed. As a result, opportunities to influence the early design and development phases, particularly in the case of Uganda, were constrained. Nonetheless, this study yielded important insights into how applying a design-by-inclusion lens can help uncover misalignments between technology design and user needs.

Finally, this study contributes to broader debates about what counts as success in AI for development. As Ahmed and Khan 2024 argue, focussing solely on model performance or scalability ignores the sociotechnical dynamics that determine real-world impact. Our integrated approach demonstrates that technical excellence must be complemented by social fit. The GEDI-informed design-by-inclusion framework offers a replicable model for ensuring that AI not only works, but works for all.

6 Conclusion

This study underscores the importance of integrating GEDI principles into the design, development, and deployment of AI tools in African agriculture. By applying a design-by-inclusion approach in two case studies in Nigeria and Uganda, we illustrate how participatory engagement with women and marginalised groups can enhance the relevance, usability, and adoption potential of AI innovations even when implemented retrospectively. Whilst our findings are based on small sample sizes and are not intended to be generalizable, they provide valuable insights into how inclusive design processes can foster user trust, build digital confidence, and promote equity in agricultural innovation. The proposed GEDI framework offers a practical guide for AI developers, researchers, and policymakers seeking to embed social inclusion into technology design. Moving forward, future AI initiatives in agriculture should prioritise co-creation with diverse stakeholders to ensure that technological progress contributes to more just, accessible, and sustainable food systems across the continent. Whilst this study highlights increased confidence and willingness to adopt AI tools, it does not measure long-term outcomes such as productivity or income. Future research should incorporate longitudinal data to track the impacts on yield, economic benefits, and sustained use over time.

7 Appendix A. Coding schema for thematic analysis

This codebook was developed and applied to the transcript data from community dialogues held in Nigeria and Uganda. The coding process was conducted by two independent researchers using NVivo 12. Codes were generated inductively from the data and later grouped into the overarching themes presented below.

See appendix Table 2

Table 2 Themes, code descriptions, and representative data extracts

Theme	Code	Code description	Example data extract (participant quotation)
Gendered Priority Misalignment	Soil_Health_Priority	Expressions identifying soil nutrient analysis and pathogen detection as a primary, unmet need	*"We can see the disease on the leaves, but we cannot see the sickness in the soil. A tool for the soil would be most helpful."* (Nagawa Robinah, female farmer, Uganda)
	Market_Price_Priority	Expressions identifying market price volatility and access as a primary concern	*"My biggest worry is not the disease, but selling my harvest at a good price. The market is very unstable."* (Sanya Julius, male farmer, Uganda)
	Pest_Detection_Met	Acknowledgement that the developed AI tool effectively addresses a key need	*"The app helps me see the bugs [pests] early so I can save my peppers. It is perfect for this."* (Ngwu Mary, female farmer, Nigeria)
Digital Access & Literacy Barriers	No_Smartphone_Access	Statements indicating a lack of ownership or regular access to a smartphone	*"I have a simple phone for calls only. This smart one for the app is too expensive for me."* (Chidinma Ugwu, female farmer, Nigeria)
	Low_Digital_Literacy	Expressions of difficulty in using smartphone features or navigating the AI app	*"I took the pictures, but then I could not find them again. It was like they disappeared into the phone."* (Edith Nnedinso, female, farmer, Nigeria)
	Data_Cost_Concern	Concerns about the affordability of mobile data required to use the application	*"If I have to buy data every time I use this, it will be a problem. My farm is far from the tower."* (Nakaggwa Sarah, female farmer, Uganda)
Impact of Inclusive Training	Fear_Before_Training	Expressions of apprehension, anxiety, or lack of confidence regarding the AI technology prior to training	*"Before the training, I was afraid of the AI tool. It seemed too complicated."* (Ugwoke Reginna, farmer, Nigeria)
	Confidence_Post_Training	Statements indicating increased self-efficacy, understanding, and willingness to use the tool after training	*"Now, after the practice, it became clear. I feel confident using it to detect pests in my crops."* (Ugwu Peace, farmer, Nigeria)
	Hands_On_Learning	Positive references to the practical, field-based approach of the training sessions	*"Going to the farm with the trainer and doing it there was the best way to learn. I remember it well."* (Benywanira Ian, female farmer, Uganda)
Shifting Agency & Empowerment	Ownership_Co-Creation	Expressions of feeling valued, heard, and involved in the development process	*"They asked us what we needed first. They listened to us women. We felt part of making this tool."* (Amuche Ezema, farmer, Nigeria)
	Desire_For_Collective_Action	Statements about forming groups or cooperatives to leverage the technology for collective benefit	*"Now that we can all detect diseases, we should form a group to sell together and get a better price."* (Namutosi Winnie, female farmer, Uganda)
	Tool_Provides_Independence	Expressions of how the tool reduces reliance on others for agricultural information	*"I do not have to wait for the extension officer to visit. I can know the problem myself now."* (Chinenye Ani, farmer with disability, Nigeria)
Contextual Relevance & Usability	Real_Time_Feedback_Value	Appreciation for the immediacy and location-independent nature of the AI tool's feedback	*"I can take a picture from where I am and know immediately. It saves me time walking the whole farm."* (Oyioh Amuche, farmer with disability, Nigeria)
	Request_LocalLanguage	Suggestions or explicit requests for the tool to be available in local languages	*"The voice in the app speaks English. If it could speak Swahili, it would be better for my mother."* (Ephraim Nuwanya, Young farmer, Uganda)
	Need_For_Simplicity	Feedback emphasising that the tool must be simple and easy to use with minimal steps	*"It is good, but it should be simpler. Just point, take a picture, and get an answer. Too many buttons are confusing."* (Eze Uchenna, elderly farmer, Nigeria)

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Declarations

Competing Interests The authors declare no competing interests.

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